USAFA TR 2000-04

Circadian Rhythm Amplitude Effects on Nocturnal Brain Electrical Activity and Mental Performance

C1C Laura Terry
Department of Biology

Dr. James C. Miller
Human-Environmental Research Center

United States Air Force Academy
Colorado Springs, Colorado 80840

May 2000

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ALICE J. CHEN, Lt Col, USAF
Director of Faculty Research

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Date

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REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. REPORT DATE *(DD-MM-YYYY)*
31 May 2000

2. REPORT TYPE

3. DATES COVERED *(From - To)*
June 1999 - May 2000

4. TITLE AND SUBTITLE
Circadian Rhythm Amplitude Effects on Nocturnal Brain Electrical Activity and Mental Performance

5a. CONTRACT NUMBER

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)
C1C Laura Terry, Dr. James C. Miller

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
Human-Environmental Research Center and Department of Biology
Dean of the Faculty
USAF Academy, Colorado 80840

8. PERFORMING ORGANIZATION REPORT NUMBER
USAFA TR 2000-04

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)

10. SPONSOR/MONITOR'S ACRONYM(S)

11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
Distribution A: Approved for public release. Distribution is unlimited.

13. SUPPLEMENTARY NOTES

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15. SUBJECT TERMS
Circadian, night work, performance, monitoring, body temperature, EEG, theta, research, military academy, USAFA, HERC

16. SECURITY CLASSIFICATION OF: a. REPORT	b. ABSTRACT	c. THIS PAGE	17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
Unclassified	Unclassified	Unclassified	Unl	25	Dr. James C. Miller
					19b. TELEPHONE NUMBER *(Include area code)* (719) 333-2804

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ABSTRACT

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INTRODUCTION

Many studies in the past half-century have been designed to understand how human fatigue causes performance to decrease. Negative repercussions stemming from this phenomenon vary in degree of damage, and numerous career fields are affected. Motor vehicle accidents increase as fatigue increases (Mackie and Miller, 1978). Three nuclear power plant incidents (at Three Mile Island, Davis-Besse, and Rancho Seco) involved human errors made during the night shift (Scott, 1994). Sleep deprivation and circadian desynchronization leading to fatigue has also been implicated as a probable cause in a number of aviation accidents (Price and Holley, 1990, cited in Gevins and Smith, 1999). Due to these destructive human errors that occur when operators are not fully alert, there is a critical need to understand the root causes of such impairments, and to develop interventions to prevent such accidents.

Fatigue has long been a topic of study for researchers from many different fields. One study associated overtime work with a variety of health and safety outcomes that may be related to fatigue (Rosa, 1995). However, most of these studies recognized that fatigue effects occurred in combination with other personal, occupational, or organizational factors and thus causality could not be determined. One undisputed trend, however, is the fact that night work hours are related to accidents (Tepas, 1994; Scott, 1994; Rosa, 1995). This trend may be attributed to the observation that the human circadian rhythm never adapts fully to night work (Scott, 1994).

F. Halberg coined the term *circadian* (from Latin *circa*, "about," and *dies*, "day") to refer to those biological rhythms that oscillate with a frequency close to the 24-h day (Scott, 1994). Many physiological, psychological, and behavioral parameters such as body temperature, cardiovascular functions, muscle strength, alertness, mood, and immediate and long-term memory follow a circadian rhythm. The technique of cosinor analysis is frequently used to fit data exhibiting varying degrees of circadian rhythm to a sinusoidal curve.

The evidence also indicates not only a critical period before dawn, but also a critical period in the middle of the afternoon when sleepiness and inattention may lead to errors that cause accidents. One algorithm produced from a combination of the population growth function and cosine function yields a distortion of the cosine curve that resembles the 24-h two peak pattern in many circadian based observations (Miller and Mitler, 1997). This distortion can be fitted to many observations and may help predict when future errors will occur. An ability to detect exactly when fatigue-related accidents might occur could be instrumental in preventing serious mishaps.

The ability of humans to acclimate quickly to changes in their work-rest schedule, relative to the local light-dark (day-night) cycle, has been investigated to some degree (e.g., Section 3 in Colquhoun and Rutenfranz, 1980). Reinberg et al. (1978) found evidence to support the contention that a low circadian amplitude in body temperature variation was predictive of quicker acclimation of body temperature ($r = -0.63$) to a 7.5-h phase shift in the work-rest schedule, relative to the day-night cycle.

All tasks are not the same regarding susceptibility to degradation by fatigue. Operational environments demanding sustained vigilance or involving multiple tasks competing for limited attentional resources (such as military fighter aircraft, air traffic controller, battle coordination, command and control etc.) are prime targets for automated monitoring. This monitoring could include continuous assessment of the mental state of the operator, measures of the degree to which attention is focused on task, and recognition of vigilance lapses and fatigue levels (Gevins *et al.*, 1995). The possible benefits of such monitoring make the results of EEG research highly significant.

Conventional human-machine or human-computer system interfaces are intended to allow the user to operate and control the system. The system in itself has no information about the amounts and types of the user's mental capacities currently being utilized, or even about the user's state of alertness. This results in a situation where the overall work efficiency and safety is less than it might be. The user could be fatigued and unable to perform all tasks presented, or the user could be under-worked, which could also lead to vigilance lapses.

Neurocognitive states can be inferred either by measuring overt performance on state-sensitive tests or by measuring physiological and neurophysiological indices thought to correlate with particular states (Gevins *et al.*, 1995). Although measuring test performance can provide useful information about changes in particular abilities, it is intrinsically intrusive and detracts from the accomplishment of competing tasks. It also does not directly provide any evidence about the subject's degree of effort. As a result of these limitations, this approach is impractical for real-time neurocognitive state assessment in operational environments.

The use of EEG to infer mental state began with Berger's original paper on the human EEG in the late 1950's (1959, cited in Wilson and Fisher, 1995). He observed that their subject's mental state was associated with changes in the nature of the EEG. In addition to widely demonstrated effects on the human EEG of eyes open versus eyes closed, the EEG can be used to determine other types of human mental state. One of the earliest observations of changes in the EEG spectrum correlated with behavior was at the transition to sleep (Makeig and Jung, 1995). The observed EEG spectrum shifts mostly towards lower frequencies. More recently, EEG has been successfully used to characterize fluctuations in vigilance (Gevins *et al.*, 1995), to index operator workload, and to predict performance degradation due to sustained mental work (Gevins *et al.*, 1990).

EEGs detect and record electrical activities via electrodes placed on the scalp (Pedley and Traub, 1990). Ideally, detection would be limited to inhibitory and excitatory postsynaptic potentials of cortical nerve cells within the brain. Unfortunately, the electrodes are also sensitive to external and internal electrical interference from sources varying from muscle activity to outdoor power lines. These influences must be screened out before any analysis on an EEG printout is performed. The electrodes are placed according to the international "10-20" naming system. This names electrodes corresponding to the underlying region of the brain. The electrodes are prefixed by the following abbreviations: prefrontal (Fp), frontal (F), central (C), parietal (P) and occipital (O). There is no central lobe but this is just used for identification purposes. A suffix of z refers to electrodes on the midline of the skull.

Increasing odd numbers correspond to electrodes descending from the midline to the left and even numbers are on the right. Discrete ranges of frequencies have been identified as recorded from EEGs and are commonly referred to in the following manner: delta (1-4 Hz), theta (4-8 Hz), alpha (8-13 Hz) and beta (13 Hz and above). A basic understanding of these terms related to EEGs is essential when discussing results of research. Here, we shall focus mainly on theta activity.

Theta waves can accompany two very different classes of behavioral outcomes: 1) in sleep deprivation studies, increased theta activity indicates a low level of alertness which results in inefficient processing of external stimuli; 2) during selective and effortful processing, theta accompanies efficient detection of stimuli (Schacter, 1977). A recent study found that a fatigue-sensitive, anatomically widespread (diffuse) theta rhythm exists that is distinct from the focal "frontal" theta rhythm affected by task difficulty (Gevins and Smith, 1999). That is, the frontal midline theta signal (5-7 Hz) was enhanced in concentration on difficult high-load tasks, whereas fatigue increases the amplitude of the diffuse theta signal. The same study found that alpha waves, 8-13 Hz, decrease in amplitude in a fatigue state as well as in a difficult high-load task. The study, however, tested fatigue associated with an alcohol hangover effect and used a working memory test. Beta waves are also positively correlated with alertness (Rechtschaffen and Kales, 1968).

The goal of the present study was to examine further the usefulness of EEG techniques used to detect CNS effects of fatigue in a simulated aviation situation. We assessed various sets of data, including body temperature data, performance data and physiological data from the EEG recordings. By investigating the interrelationships among these measures, we hoped to further the foundation for designing a measure to warn against performance impairments before costly accidents occur.

The sixteen subjects involved in this study participated in an overnight testing session during which they performed the Multi-Attribute Task Battery (MATB) at the highest workload level possible. We expected the following results:

- Based upon a very large body of relevant research literature, the subjects should have displayed circadian rhythms in body temperature and in performance, primarily for monitoring tasks, across the night. Thus, many performance errors should have occurred around 0300, corresponding approximately with a body temperature nadir.
- The EEG was expected to show decreases in alertness several hours before performance decreased (Gevins et al., 1990). A decrease in amplitude of the alpha rhythm should have occurred as the subjects became sleepier, and decreases in frontal midline theta activity should have occurred with decreases in performance requiring concentration throughout the night. We also expected increases in diffuse theta with increasing fatigue.
- Based upon the findings of Reinberg et al. (1978), we divided the subjects into two groups, one with very little circadian amplitude in their body temperature variation and one with greater circadian variation. We expected the group with the smaller circadian variation to perform better during the nocturnal testing sessions.

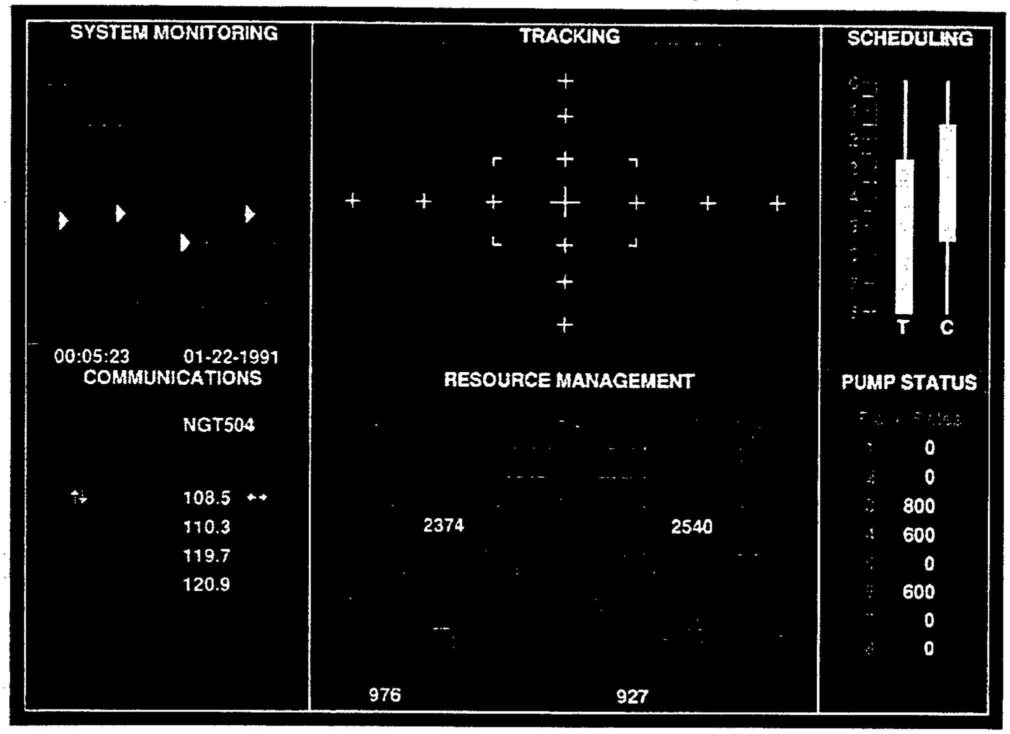
METHODS

Subjects. The experiment on fatigued subjects was part of a larger experiment testing the effects of various conditions (also including alcohol, antihistamine and nicotine) on concentration. This study was designed and conducted by investigators at EEG Systems Laboratory (EEGSL) in San Francisco, CA. Dr. Michael Smith of EEGSL provided the data discussed here to C1C Terry during her USAFA Cadet Summer Research Program internship (CSRP; Summer 1999) at EEGSL. The volunteer subjects were sixteen healthy adults (8 female, 8 male) ranging in age from 21 to 32 years, all of whom provided informed, voluntary consent to participate in the study.

Tasks. The data analyzed and reported here came from an overnight testing session where the subjects performed the Multi-Attribute Task Battery (MATB; shown, below) at the highest workload level possible. This task was similar to a flight simulation and was made up of four independent subtests. Each subtest was contained in a window in a portion of a computer screen, and subjects were required to attend to each simultaneously. The tracking window consisted of a joystick-controlled target that the subject was required to keep as close to the center as possible (sub-critical tracking). In the high workload level, the target strayed a great deal from the center. A monitoring window required the subject to respond if warning lights turned on or off or if gauges strayed from beyond their designated areas. There were 35-40 necessary gauge/warning light responses (approximately 20 of each) in each trial. The resource management window simulated six separate fuel tanks that delivered fuel to one another. Subjects manipulated the flow of fuel to and from eight different areas that ultimately fed the primary fuel tanks. The subjects were instructed to maintain the fuel level of the primary tanks at a precise number of units. At the high workload level, 10 pumps failed during the trial. Finally, a communications subtest required the subject to listen and respond to audio messages from a simulated Air Traffic Controller. Subjects listened for their callsign among a number of others that were called and followed the instructions given. Upon hearing their callsign, subjects were told to change navigation and communication frequencies. During the trial, 10 of each ("response" and "no-response" calls) were presented.

The investigators collected data regarding all aspects of the tasks throughout the testing sessions. Six objective measures of performance were calculated for each subject along with two subjective, self-reported measures. *Tracking Deviation* referred to the mean number of pixels of aircraft drift away from the target rectangle for each subject during each session. The lower the value the higher accuracy that the subject had over the session.

Multi-Attribute Task Battery Display



Monitor Response Time referred to the monitoring of the gauges and lights in the monitoring window. The value for each subject during each session reflected the average response time, i.e., how quickly they responded to changes that required action. *Monitor Error Percent* also referred to the monitoring window. The values reflected accuracy and were calculated as the number of errors in responding to problems with the lights and gauges divided by the total number of monitor stimuli. Monitor errors included time outs (failure to respond to/ correct a problem with the lights and gauges of the aircraft) and false alarms (responding when there was no problem).

Resource Management Mean Deviation referred to the average absolute deviation of the fuel tank levels from the ideal level of 2500 units in the resource management window, i.e., if the level went up to 3000 or down to 2000, the deviation would have been 500. The levels were recorded every 30 seconds and the deviations were averaged across the length of the trial (5 minutes).

Communications Response Time referred to responding to the communication subtask. The response time for each subject during each session was the mean of how quickly the subject responded to the auditory stimulus. *Communications Error Percent* was calculated as the

number of communication errors, over the total number of communication stimuli. Errors included responding incorrectly to a call sign, responding to the wrong call sign, and failing to respond to the correct call sign.

Workload was a rating the subjects completed directly following a testing session. Subjects were first asked to rate Mental Demand, Physical Demand, Temporal Demand, Effort, and Frustration on a Low-High scale (moving a cursor between the 2 extremes on a scale). A second rating was the subject's assessment of their performance on a subjective scale of Good-Poor. These two ratings were then weighted and combined to produce the workload rating number.

Training and Testing Procedures. The subjects practiced all tests until they reached proficiency. This tended to eliminate the effects of learning in the results. The training session included completion of five sessions of each of three levels of the test in increasing difficulty (low, medium, high workloads). They then completed seven each of the medium and high levels. Finally, they rotated through two sets of all three levels. To collect the fatigue data, subjects were brought in for an overnight recording session. The first block of the test began after subject preparation (2230 – 2300). The second block began at 0030, the third at 0130, the fourth at 0300, and the last began at 0500. The subjects performed several different tasks related to other portions of the experiment during each block, but completed each block with the MATB task. Electroencephalographic (EEG) data were recorded from 28 scalp locations, and an electronically linked mastoid reference was used. To determine oculomotor activity, vertical and horizontal eye movements were recorded. Impedances on the reference electrodes was reduced to less than 5 KΩ and brought below 20 KΩ on all other channels prior to recording.

Data Reduction. Before leaving the lab, C1C Terry performed several required manipulations of the EEG data using software developed by the lab (MANSCAN). The manipulations were identical to those used by the lab investigators for other portions of the data set (Smith, 1999). The continuous data were passed through an initial, analog band-pass filter of 0.01 to 100 Hz and sampled at 256 Hz. Eye movement artifacts were corrected with a method designed by the lab using MANSCAN software. All data was visually inspected and any residual contaminants not picked up by the software were manually marked and not used in subsequent analyses. Fast Fourier transforms were calculated for all two-second contaminant-free EEG segments from each subject and then averaged across all trials to produce summary power spectra. After these data were inspected, subject-specific features of selected frequencies were extracted. These data were converted to within-subject z-scores so that data could be compared easily across subjects.

RESULTS AND DISCUSSION

Temperature. We used cosinor analysis to reduce the temperature data obtained from the subjects (Naitoh et al.1985). Inspection of the results from all subjects revealed several anticipated characteristics about the data. First, the average time for the acrophase was as expected for day worker-night sleepers, i.e., in the late afternoon. The percent of total variance explained by the circadian model was about as expected (e.g., Miller et al., 1999). Finally, the mesor was about as expected for normal human body temperature.

The initial inspection of the results also indicated that the data could be divided into two groups based upon the percent of total variance the algorithm estimated was due to circadian rhythm. The high group (group A) consisted of subjects with more than 10% of the variance explained by the cosine function, and the low group (group B) with less than 10% of the variance explained by this function. The results of important aspects of the analysis of all subjects are shown in Table 1, along with the two groups (A and B) described previously. We used groupings A and B in subsequent analyses of performance and EEG data.

TABLE 1. Circadian characteristics of subjects based on cosinor analysis of body temperature: mean, standard deviation and coefficient of variance. *Not reported due to small circadian variation.

Group	n		Cosinor Mesor	Amplitude	Acrophase	Variance due to Circadian
All Subjects	16	Mean	96.9°F	0.356	18:18	19.1%
		Std. Dev.	0.89	0.313	4.25 hr	13.4%
		Coeff. Var.	0.0092	0.879	0.232	0.703
A. Var. > 10%	10	Mean	96.7°F	0.511	18:22	27.9%
		Std. Dev.	0.82	0.299	3.63 hr	7.8%
		Coeff. Var.	0.0084	0.584	0.198	0.279
B. Var. < 10%	6	Mean	97.0°F	0.099	*	4.3%
		Std. Dev.	1.06	0.082		3.2%
		Coeff. Var.	0.011	0.831		0.745

The circadian temperature characteristics of groups A and B were clearly different from those of the all-subjects group. The group A percent of variance explained by the cosine function was greater by a factor of nearly 1.5 than for all subjects. Group B had a very small variance explained by the cosine function (a factor of eight less than group A).

The coefficient of variation standardizes the various standard deviations among the different groups. The lower the coefficient the less relative variance there is in that measure. The coefficient of variation for the amount of variance explained by the cosine function was smaller by a factor of two for group A, compared to group B. The mean amplitude of group A was, by design, larger than that of the all-subjects group while the subjects in group B had the smallest mean amplitude. This is reasonable since the smaller the circadian amplitude, the more difficult it is to detect the circadian rhythm.

Two subjects placed into group B had acrophases that did not fall within the expected 1200-0000 period. Most likely, the small amplitude of their circadian variation in body temperature precluded the cosine algorithm from calculating accurate acrophases. An inspection of the data in group B reveals that the standard deviations are almost as large as the mean, indicating a lack of consistency in the data. With only 4% of the variance in this group attributed to circadian rhythm, it would be difficult to describe their data in terms of circadian-rhythm characteristics, especially acrophase.

Performance Data. The results of a mixed design, 2-factor, 2 x 5-level analysis of variance with repeated measures across sessions, using program BMDP2V, are presented in Table 2 for each performance measure. Initially, we used an alpha value of 0.05 (95% confidence interval) in determining significance. However, we also examined an alpha of 10%. Statistically significant results are marked in Table 2 and shown in Figures 1 through 3.

TABLE 2. The results of the mixed design analysis of variance for each performance measure. The F values, mean square error (MSE), p-value, and Greenhouse-Geisser probability (to correct for repeated measures; in parentheses) are shown. Statistically significant results are marked (*p < 0.10, **p < 0.05).

Performance Measure	**Group Effect** df=1,13	**Session Effect** df=4,52	**Session by Group Interaction** df=4,52
Average Tracking Deviation	F = 0.69 MSE = 1915.126 p = 0 .422	F = 1.63 MSE = 49.0972 p = 0.180 (0.216)	F = 0.77 MSE = 49.0972 p = 0.149 (0.193)
Monitor Response Time	F = 0.24 MSE = 2.666 p = 0.631	F = 3.26 MSE = 0.257 p = 0.0186 (0.0251**) *(Figure 1)*	F = 1.61 MSE = 0.257 p = 0.185 (0.195)
Monitor Error %	F = 0.06 MSE = 0.00482 p = 0.808	F = 2.28 MSE = 0.00218 p = 0.0761 (0.1197)	F = 1.37 MSE = 0.00218 p = 0.259 (0.294)
Communication Response Time	F = 0.82 MSE = 4.617 p = 0.381	F = 0.46 MSE = 0.302 p = 0.766 (0.682)	F = 0.96 MSE = 0.302 p = 0.439 (0.413)
Communication Error Percent	F = 1.07 MSE = 0.0121 p = 0.319	F = 1.03 MSE = 0.00368 p = 0.403 (0.397)	F = 2.36 MSE = 0.00368 p = .0654 (0.0761*) *(Figure 2)*
Resource Management Mean Deviation	F = 0.4.88 MSE = 26104.3 p = 0.0458** *(Figure 3)*	F = 0.96 MSE = 4360.1 p = 0.436 (0.400)	F = 0.91 MSE = 4360.1 p = 0.467 (0.423)
Workload	F = 0.26 MSE = 1984.027 p = 0.6171	F = 130.714 MSE = 0.130.714 p = 0.1707 (0.1956)	F = 16.477 MSE = 78.217 p = 0.9314 (0.8668)

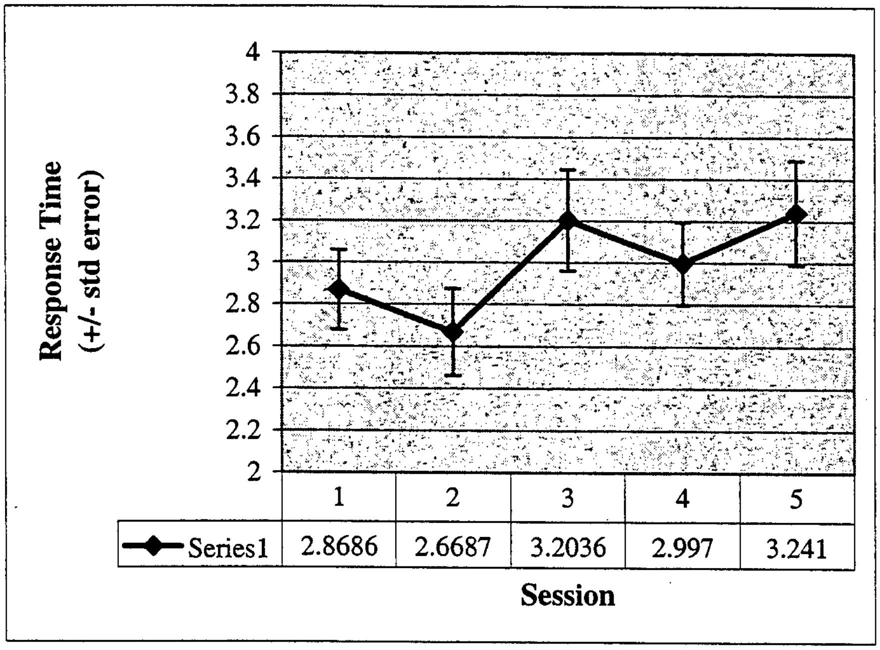


Figure 1. Session effect on monitor response time.

Figure 1 shows the mean response time for monitoring across sessions. It appeared that response time increased significantly between the second and third recording session: between the 0030 session and the 0130 session there was approximately a 1-second mean increase in time to respond to display changes. Increasing response time across sessions is often observed for vigilance tasks (e.g., Miller and Mackie, 1980).

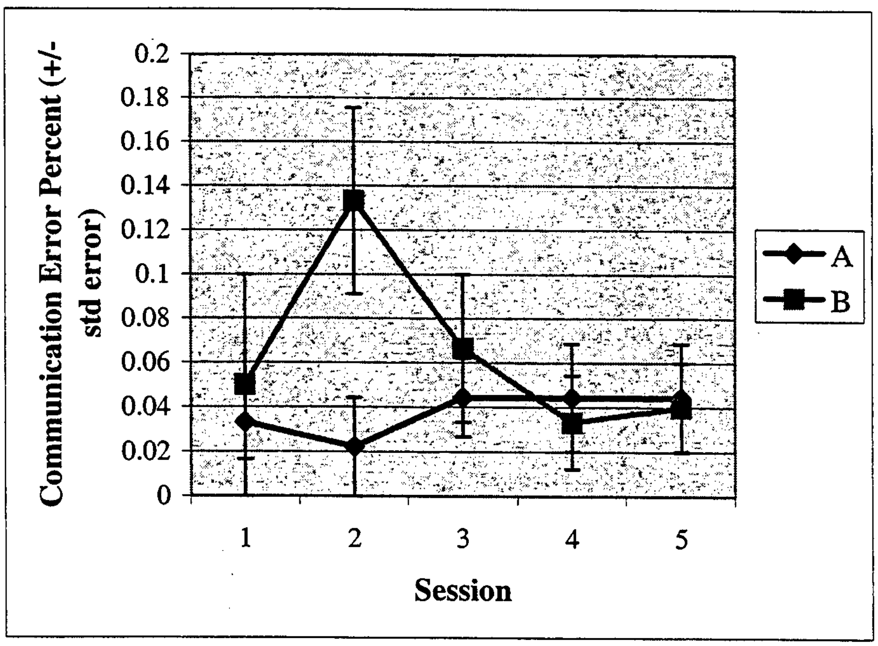


Figure 2. Session by group effect on communication error percent.

Figure 2 shows the group effect on communication error percent across sessions. Group A's performance remained constant across the session in responding to the auditory stimulus. Group B, on the other hand, had a large spike in errors during the 0030 session and then the error percent dropped back down to levels similar to Group A.

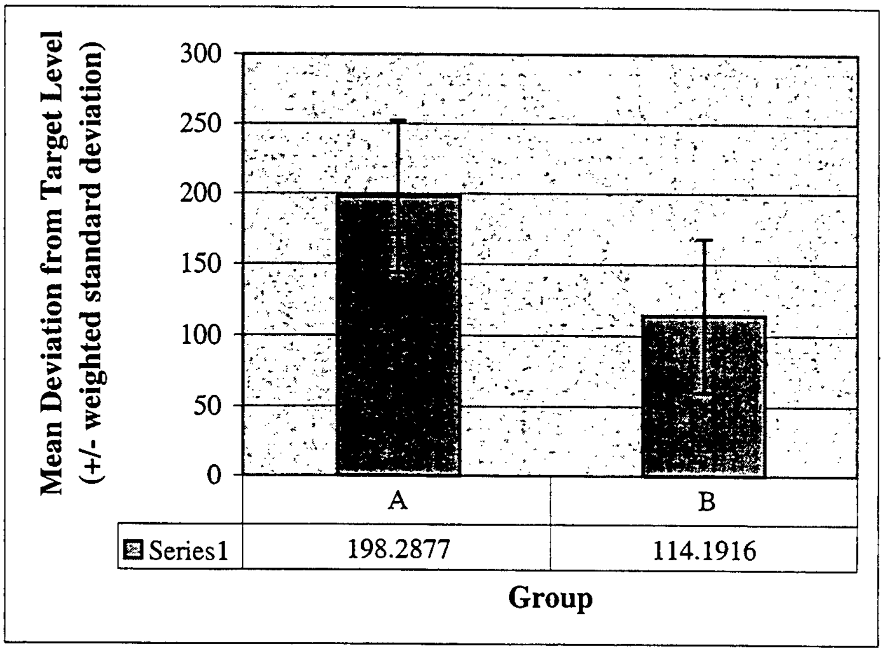


Figure 3. Group effect on resource management mean deviation. Notice the greater deviation observed in group A, those subjects exhibiting stronger temperature fluctuations throughout the night.

Figure 3 shows the significant difference between Groups A and B for resource management mean deviation. The subjects were grouped based upon the estimated strength of circadian rhythm from body temperature recordings. Group A includes those subjects who had strong temperature deviations throughout the night, such that a cosinor curve could be fitted reasonably well to their data. This group had a significantly greater deviation in the resource management portion of the task than did their counterparts with weaker circadian rhythms. This is reasonable, as it has been suggested that strength of circadian rhythm has an effect on performance throughout the night (Reinberg et al., 1978).

Figure 4 shows that the monitor error percent increased significantly between 0130 and 0300. Technically, this result was not quite statistically significant ($p = 0.1197$). However, we show it here because it demonstrated interesting changes and approached significance. We expected this finding based upon studies concerning vigilance performance when fatigued. As the subject becomes less alert, he or she is more likely to miss a subtle change in the system being monitored (e.g., Miller and Mackie, 1980), providing highly variable performance. This session effect was the only effect in the performance data set that showed the expected circadian pattern, i.e., a reversal after 0300.

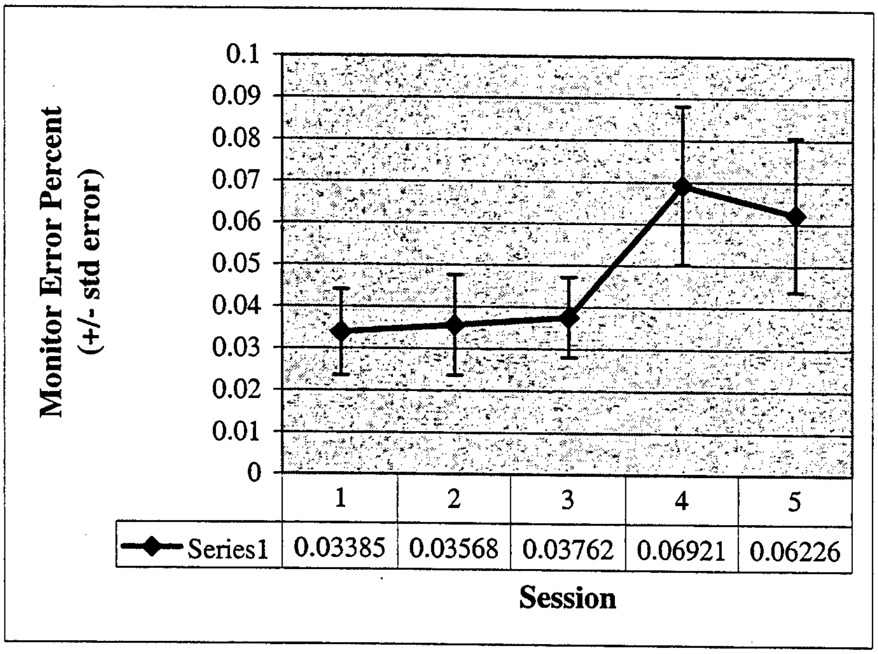


Figure 4. Session effect on monitor error percent. Notice the dramatic increase between session 3 and 4, corresponding to the time between 1:30 and 3:00 a.m.

EEG Data. The results of a mixed design, 2-factor, 2 x 5-level analysis of variance with repeated measures across sessions, using program BMDP2V, are presented in Table 3 for each EEG measure. We used an alpha value of 0.05 in determining significance. We then reanalyzed the significant effects found in the raw power using within-subject standard (z) scores. Statistically significant results in the latter are marked (**$p < 0.05$), below, and summarized in Table 4.

TABLE 3. The results of the mixed design analysis of variance for each EEG measure. The F values, mean square error (MSE), p-value, and Greenhouse-Geisser probability (to correct for repeated measures; in parentheses) are shown. Statistically significant results in the latter are marked (**p < 0.05).

EEG Measure	**Group Effect** df=1,14	**Session Effect** df=4,52	**Session by Group Interaction** df=4,52
Delta @ Cz	F = 0.54 MSE = 226.821 p = 0.474	F = 0.34 MSE = 0.4768 p = 0.852 (0.789)	F = 0.46 MSE = 0.4768 p = 0.763 (0.701)
Delta @ Pz	F = 0.15 MSE = 235.271 p = 0.707	F = 0.65 MSE = 0.6806 p = 0.630 (0.564)	F = 0.19 MSE = 0.6806 p = 0.942 (0.873)
Theta @ Fz	F = 4.96 MSE = 73.6720 p = 0.0428**	F = 9.94 MSE = 0.7386 p = 0.0000 (0.0001**)	F = 1.93 MSE = 0.7386 p = 0.1184 (0.1496)
Theta @ Pz	F = 1.03 MSE = 21.7260 p = 0.3295	F = 2.23 MSE = 0.3292 p = 0.0782 (0.1008)	F = 0.24 MSE = 0.3292 p = 0.9133 (0.8642)
Alpha1 @ Pz	F = 0.03 MSE = 58.4345 p = 0.8550	F = 3.07 MSE = 0.4011 p = 0.0242 (0.0415**)	F = 0.61 MSE = 0.4011 p = 0.6584 (0.6072)
Alpha2 @ Oz	F = 0.08 MSE = 18.2592 p = 0.7838	F = 0.55 MSE = 1.3102 p = 0.6978 (0.5368)	F = 0.55 MSE = 0.7233 p = 0.6984 (0.5372)
Beta1 @ Pz	F = 3.96 MSE = 10.1097 p = 0.0682	F = 1.75 MSE = 0.2694 p = 0.1535 (0.1963)	F = 0.29 MSE = 0.2694 p = 0.8834 (0.7379)
Beta2 @ Pz	F = 6.53 MSE = 9.2337 p = 0.0239**	F = 4.85 MSE = 0.6245 p = 0.0021(0.0076**)	F = 1.18 MSE = 0.6245 p = 0.3323 (0.3304)

TABLE 4. Summary of significant group and session effects on EEG measures, shown as means of within-subject standard scores.

Variable		**Group A**	**Group B**			**p**
Theta @ Fz		29.36	33.77			0.0428
Beta2 @ Pz		18.88	20.71			0.0239
Variable	**Session 1**	**Session 2**	**Session 3**	**Session 4**	**Session 5**	**p**
Theta @ Fz	-0.848	-0.393	0.038	0.340	0.859	<.0001
Slow Alpha @ Pz	-0.455	-0.0076	-0.0294	-0.239	0.671	0.0242
Beta @ Pz	-0.572	0.116	-0.326	0.672	0.110	0.0033

Figure 5 illustrates the difference in mean raw power between group A and group B of Theta measured at Fz. Group A, those with stronger circadian rhythms in body temperature, had a smaller amount of theta power than those in group B. The range of mean raw power for group A was 25.27 to 31.23 while the range for group B was 25.96 to 32.04. Frontal theta

is probably associated with focused attention and working memory. It is possible that those with smaller-amplitude circadian rhythms (group B) suffered relatively less from sleepiness or the malaise of fatigue when forced to perform night work. Thus, their working memory may have been more intact, as indicated by the greater frontal theta amplitude.

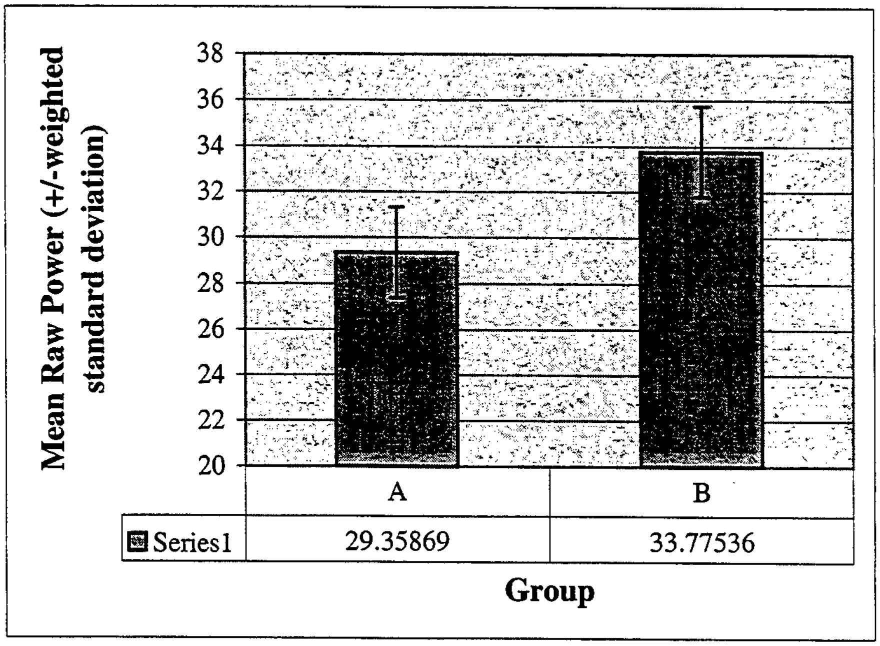


Figure 5. Group differences in EEG theta measured at Fz.

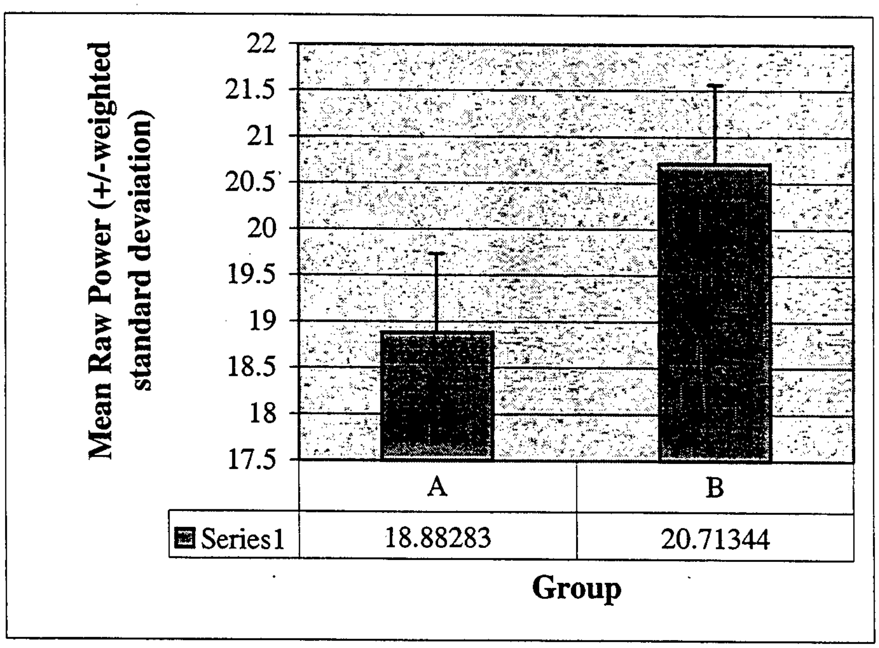


Figure 6. Group differences in EEG beta2 (20-30 Hz) measured at Pz.

Figure 6 shows the difference in mean raw power between Group A and Group B for beta2 measured at Pz. It shows a pattern similar to the group difference found in theta. The range in raw power for Group A was 17.55 to 20.61 and for Group B was 19.18 to 24.35. Beta has been shown to be associated with alertness (cf. Rechtschaffen and Kales, 1968). Thus, the explanation for the greater amplitude beta2 in of group B may be the same as that for the greater theta amplitude.

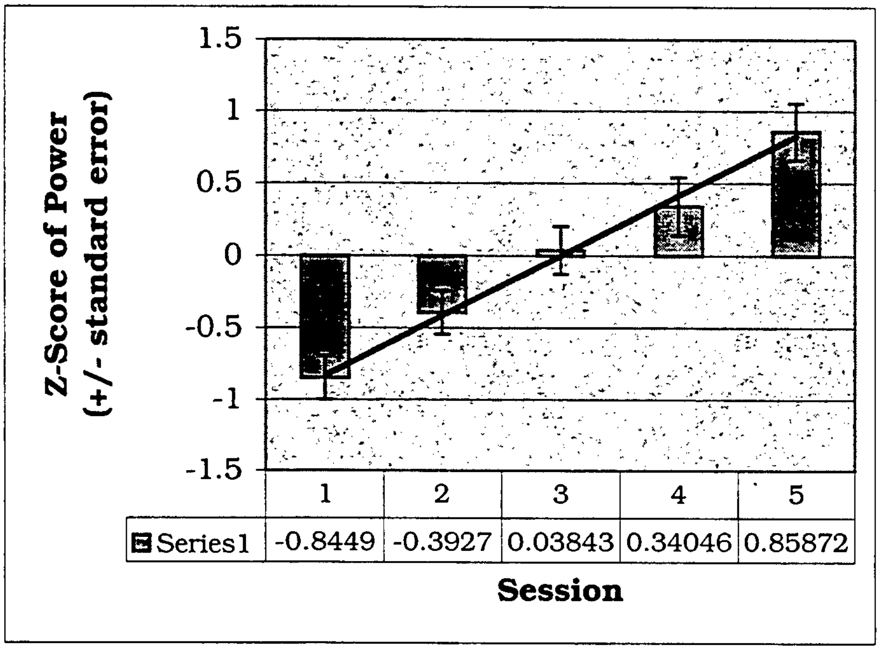


Figure 7. Session effect on theta measured at Fz. The dark line is the linear regression line fitted to the means.

The session effect on theta is shown in Figure 7. This session effect is puzzling. Generally, we would expect to see a decrease of theta across the night due to acute fatigue and to circadian fluctuation. However, two types of theta have been observed to be involved with fatigue. The first type is theta found near the frontal midline area. As this measurement was taken at Fz, Figure 7 would most likely be representative of this component. Increases in frontal theta activity are associated with increases in focused attention. The other type is a diffuse theta that increases with fatigue. We would expect to see parallel increases in theta across sessions at other scalp locations if we were picking up a diffuse increase in theta. However, since no other points showed significant increases across sessions, it seems that the first option is a better explanation of the data.

Figure 8 shows a significant difference in alpha measured at Pz between the first session (2330) and the fifth session (0500). Most likely, the subjects started the night in an alert state and the alpha increase indicated the increasing presence of "relaxed wakefulness" (e.g., Rechtschaffen and Kales, 1968) as fatigue set in.

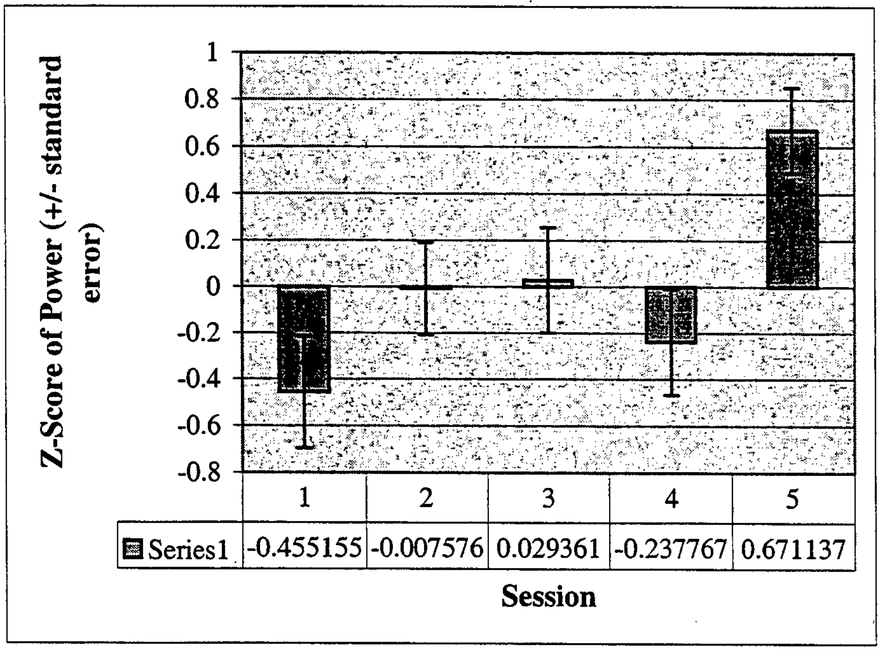


Figure 8. Session effect on slow alpha measured at Pz.

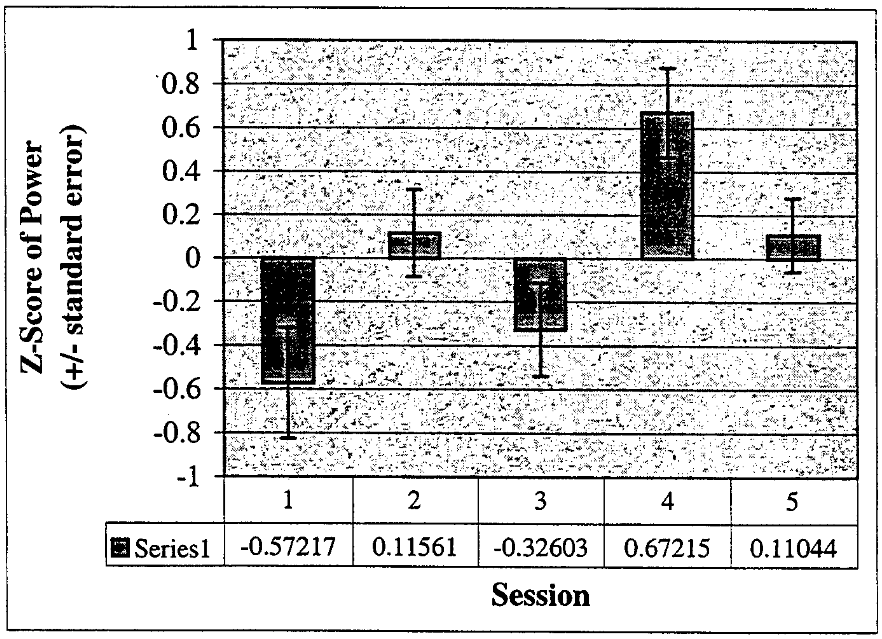


Figure 9. Session effect on beta2 (20-30 Hz) measured at Pz.

Figure 9 shows the session effect on Beta2 at measured at Pz. It is apparent that, overall, the power of beta at Pz was much greater during the 0300 session (Block 4) than during the initial session at 2330 (Block 1). This session effect was the only effect in the EEG data set that showed the expected circadian pattern, i.e., a reversal after 0300. However, this pattern did not support our second hypothesis. Beta is usually dominant in the alert state when other waves (alpha, sleep spindles, and delta) are absent, and should decrease with increasing

sleepiness. These data suggested that the subjects were expending the greatest effort to concentrate at 0300.

Correlational analysis. Since the purpose of this study was to determine the feasibility of predicting performance (or a lack thereof) using the EEG, correlations were computed across sessions between the grand session means of significant changes in performance and the grand session means of significant changes in the EEG. These grand session mean correlations should represent fundamental relationships, with intersubject contributions to variance minimized. We used a cutoff of r^2 equal to 50% in determining significance. Thus, the EEG pattern across sessions was required to explain at least half of the variance in performance. The results are shown in Table 5.

TABLE 5. Correlation coefficient (Pearson r) between the predictor (EEG) and dependent variable (performance). Value in parenthesis indicates the coefficient of determination, r^2, the percent of variability in performance accounted for by differences in EEG (*$r^2 > 0.5$).

	Monitor Response Time	**Monitor Error Percent**
Theta at Fz	0.728 (0.530)*	0.819 (0.671)*
Slow alpha at Pz	0.573 (0.320)	0.381 (0.145)
Beta2 at Pz	-0.011 (0.0001)	0.813 (0.661)*

There were three significant correlations between EEG changes and performance changes across the sessions. Two significant correlations involved theta at Fz. In each, as theta increased, performance decreased. The third significant correlation was between beta2 and monitor error percent. Generally, beta activity and frontal midline theta activity are correlated with effortful concentration. The results suggested failing efforts by the subjects.

CONCLUSIONS

We hypothesized that the *subjects would display circadian rhythms in body temperature and in performance, primarily for monitoring tasks, across the night.* Thus, many performance errors should have occurred around 0300, corresponding approximately to the occurrence of a body temperature nadir. This first hypothesis was supported by the data. There were easily recognized circadian patterns in body temperature and in monitoring performance.

We found a wide rage of strengths of circadian variation in body temperature, as estimated using cosinor analysis. The cosinor-estimated nadirs occurred around 0620 (acrophase in Table 1 minus 12 hours), somewhat later than we expected. This observation suggested that the circadian rhythms of body temperature in the sample of subjects were somewhat phase delayed with respect to the day-night cycle.

We found that the mean response time for the monitoring task, a task with a strong vigilance component, increased monotonically across the five nocturnal testing sessions (Figure 1). Since the metabolic nadir of the subject sample was, apparently, delayed as late as 0620, then these vigilance performance data may simply have reflected the expected performance decline associated with body temperature decline approaching the circadian nadir.

In light of the preceding observation, the apparent reversal at 0300 of errors in monitoring (Figure 4) was probably a sampling error. Note that the error bars plotted for sessions 4 and 5 (0300 and 0500, respectively), were quite large compared to the earlier sessions. It is likely that monitoring errors also reflected the expected performance decline associated with body temperature decline approaching the circadian nadir.

The statistically significant effect of session on communication error percent did not reflect a recognizable circadian pattern. The error peak at 0030 for the low-amplitude group (group B; Figure 2) seemed anomalous.

Overall, our EEG data suggested monotonically increasing levels of fatigue, sleepiness and effort across the night. We hypothesized that a *decrease in amplitude of the alpha rhythm would occur as the subjects became sleepier.* In fact, there was a significant, nearly monotonic increase in alpha activity across the night, measured at the midline above parietal cortex (Pz; Figure 8). We were forced to reject our hypothesis in favor of the speculation that the subjects started the night in an alert state and that the alpha increase indicated the increasing presence of "relaxed wakefulness" as fatigue set in.

We hypothesized that a *decrease in frontal midline theta activity would occur with decreases in performance requiring concentration throughout the night.* In fact, in the absence of a significant effect of session on theta measured at Pz, there was a significant effect of session on theta activity measured at the midline over frontal cortex (Fz; Figure 7). The seeming isolation of the effect on theta in frontal cortex forced us to conclude that this frontal theta activity was, in fact, associated with focused attention. The effect was so strikingly monotonic that we were able to fit a least-squares linear regression line easily to the group

means across sessions. Thus, it appeared that the effort to concentrate increased linearly across the night.

Assessing the results of an investigation of truck drivers operating on the highway at varying times of day and night, Mackie suggested that EEG characteristics seemed to reflect effort, rather than sleepiness (Mackie and Miller, 1978). He reasoned that, although subjects who must operate a system during the pre-dawn nadir in metabolic function, following a night of sleep deprivation or truncation, may report subjective perceptions of fatigue and sleepiness, their EEG may reflect the effort required to overcome that malaise to operate the system successfully. We add that, if true, this may be a transient occurrence: as fatigue progresses, subjective perceptions of fatigue and sleepiness may precede evidence of fatigue in the EEG. Subsequently, in more extreme fatigue states, the EEG, itself, reflects the degree of fatigue (Gevins et al., 1990)

We hypothesized that an *increase in diffuse theta would occur with increasing fatigue*. We did not see parallel session effects on theta activity at diffuse scalp sites. Thus, we concluded that these subjects did not become extremely sleepy as a result of remaining awake and performing mental tasks during one night of sleep deprivation. The monotonic alpha increase suggested the development of mild sleepiness.

We hypothesized that the *EEG would show decreases in alertness several hours before performance decreased.* There was no obvious evidence in the data set to support this conclusion. If the preceding conclusion about diffuse theta is true, then it is possible that the subjects did not become fatigued or sleepy enough for this predictor effect to be revealed.

We hypothesized that the *group with the smaller circadian variation in body temperature (group B) would perform better than the other group during the nocturnal testing sessions.* This hypothesis was supported by the data. Group B demonstrated a significantly smaller mean tracking deviation than group A (Figure 3), lending at least minimal support to this hypothesis. In parallel, group B demonstrated greater frontal EEG theta power than group A (Figure 5). This observation suggested a greater presence of focused attention in group B during the night. Similarly, group B demonstrated a significantly greater amount of EEG beta activity during the night (Figure 6), suggesting a higher level of alertness that group A.

There were three significant correlations among the significant session effects on EEG and performance: two between theta at Fz and two performance indicators, monitor response time and monitor error percent, and the third between beta2 and monitor error percent. As beta and frontal theta increased, performance on the monitoring task decreased. We speculate that the observed relationships between EEG activities and monitoring performance may have reflected the effort required to overcome the effects of fatigue-induced malaise to operate the system successfully.

Many factors contribute to performance in a multiple task environment. Additional factors come into play in an operational environment. Though simplistic relative to an operational setting, this study yielded several interesting results. First, there were significant differences between groups in EEG activity and performance related to the strength of the circadian

variation in body temperature. Second, there were changes in EEG activities and performance across the night that suggested interesting relationships among EEG activity, monitoring performance and effort. Overall, the study supported the hope of one day using the EEG to detect changes in mental state.

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